Disaggregate residential choice models

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DISAGGREGATE RESICENTIAL CHOICE MODELS
REVIEW AND CASE STUDY

Wal F.J. van Lierop
Peter Nijkamp

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Abstract

This paper aims at providing an operational framework for housing market research by means of disaggregate choice analysis. First, a concise survey of spatial choice and interaction models is presented, starting from a systematic typological approach. Then the advantages of disaggregate spatial choice models (especially probit models) are pointed out. Next, the paper presents extensively empirical results obtained from the application of a disaggregate residential choice model based on a probit analysis to the Dutch housing market. The analysis is based on a multi-step procedure, viz. the assessment of the prior propensity to move, followed by the assessment of the (conditional) probability for an actual move into a specific dwelling type. Brief attention is also paid here to spatial differences in moving behaviour.

Authors' address:

Free University
P.O. Box 7161
1007 MC Amsterdam
The Netherlands

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1. INTRODUCTION

The housing market is a multi-faceted and heterogeneous market characterized among other things by: complex search and choice processes of (potential and actual) movers, diversity in information content regarding supply and demand on various sub-markets, drastic shifts in locational behaviour due to structural economic changes, strong impacts of social and geographical spillover effects (e.g., segmentation, environmental quality), occurrence of disequilibria on various sub-markets (due to inertia in public decision-making, socio-economic and demographic changes, strong land use competition, etc.), and high degree of public and institutional interference.

In the past, a wide variety of housing market models has been developed and applied in order to investigate the abovementioned complexity in residential choices (see, for instance, Anas, 1976; Bird, 1976; Clark and Smith, 1982; Evans, 1973; Huff and Clark, 1978; Kain and Quigley, 1970; Kain et al., 1976; Van Lierop and Nijkamp, 1985; Putman, 1979; Richardson, 1977; Simmons, 1974; Stahl, 1980; Wegener, 1980; and Wilkinson, 1973). A representative description of various housing market analyses can also be found in Clark and Van Lierop (1986) and Porell (1982).

The present paper deals mainly with one aspect of the housing market: it aims at providing an operational framework for disaggregate residential choice models for housing market analysis. By way of introduction, first a brief typology for spatial choice models will be given (section 2), followed by a concise survey of spatial choice and interaction models (section 3). Then the advantages of disaggregate spatial choice models will be pointed out, followed by a justification of the use of a multinomial probit model (section 4). The remaining sections (5 and 6) are devoted to a description of the Dutch housing market and discussion of various empirical results obtained by means of a disaggregate residential choice analysis of this market based on a probit model.

2. A TYPOLOGY FOR SPATIAL CHOICE MODELS

Spatial choice models focus attention on a formal analysis of spatial location and allocation decisions of individuals and groups. Such models aim at portraying and forecasting spatial processes and choice patterns in complex geographical systems (see, Van Lierop and Rima, 1985). The design of such models requires (a) insight into cause/effect links in a complex spatial system, (b) an identification of key factors of spatial choice behaviour, (c) a consideration of exogenous factors and public institutional measures, and (d) a specification of the range of feasible choice options.

In general, the set of spatial choice models is highly differentiated. The following criteria for a typology of spatial choice models may be used:

(a) the level of aggregation (individuals, groups, nations, etc.). Conventional spatial choice and interactions models tended to be aggregate in nature, but in the past decade the main stream of spatial interaction analysis has increasingly focused attention on disaggregate spatial choice models (see, for example, Harsman and Snickars, 1975; Van Lierop and Nijkamp, 1980, 1982; McFadden, 1978; and Van Lierop, 1976).

(b) the nature of the choice process. According to Manheim (1979) choice processes are multidimensional: multitemporal, multi-problem oriented, multi-sectoral,multi-person and multi-disciplinary. In this regard, it may be meaningful to make *inter alia* a distinction between: preference analysis and perception analysis (cf. Blommestein et al., 1981), latent motives and actual decisions of actors in space, search behaviour and choice behaviour (cf. Huff, 1982), descriptive and explanatory choice analysis, and demand constraints (income, location, family size, social control such as Veblen effects, etc.) and supply constraints (supply of infrastructure, market information, institutional regulations, etc.).

(c) the element of time. Spatial search and decision processes are usually non-static, while they also exhibit learning aspects (see for instance, Weibull, 1978; De Palma and Ben Akiva, 1981; and Clark and Smith, 1982). Such dynamic processes may be due to either exogenous shifts (changes in general mobility patterns, for example) or endogenous decisions of actors (e.g.,mental processes, saturation effects). In recent years, panel and longitudinal analyses have become increasingly popular ways of observing consumer behaviour over a longer period (see for instance, Golob et al., 1984). Very recently, also event history analysis has become an important tool for studying expectations of actors with regard to their income, time budget, mobility pattern, desired location, family size, etc. As panel and longitudinal studies are usually extremely expensive, an intermediate strategy may be found by holding a household inquiry at two successive points in time, so that discrete shifts in perceptions and preferences can be analysed. In addition, this approach can be used to assess real conditional space choice probabilities in the second period, given the information on spatial choice preferences and perceptions from the first period. The latter strategy will be adopted in the empirical part of this paper.

(d) the attributes of the choice items. Choice items (for example, dwellings) are normally heterogeneous in nature: dwellings exhibit a wide variety regarding age, size, quality, rent, accessibility, neighbourhood quality, distance to amenities, etc. The multidimensional nature of spatial choice items hampers a straightforward assessment of related demand functions, so that a more refined analysis and inventory of choice items is needed, based on a detailed multi-attribute approach. The way in which such a multi-attribute analysis of choice items can be operationalized will be described in greater detail in the empirical part of this paper.

The abovementioned typology of spatial models forms also the background for the succinct review of main classes of such models in the next section.

3. A BRIEF SURVEY OF SPATIAL CHOICE AND INTERACTION MODELS

The "geography of movement" (Lowe and Moryades, 1975) has been followed by the design and use of a wide variety of spatial choice and interaction models, some of them being macro and mechanical in nature, others being micro- and behavioural-oriented. The following major classes of aggregate (macro) and disaggregate (micro) spatial choice and interaction models may be mentioned:

A. Aggregate Models

(a) Programming models: These models describe mainly location-allocation patterns in a spatial system, based on aggregate cost or utility functions (see for instance, Dendrinos, 1980; Herbert and Stevens, 1960; or Ingram et al., 1972).

(b) Gravity and entropy models: This class of models became very popular in the seventies, in particular since it could be demonstrated that the rather mechanical nature of these location-allocation models could be provided with a more solid statistical and behavioural meso foundation (see Wilson, 1973; and Nijkamp, 1979). The majority of these models is aggregate and describes equilibrium conditions for a spatial system driven by repulsive and attractive factors.

(c) Catastrophe and bifurcation models: These models aim at studying the behaviour of dynamic spatial systems mainly by means of differential topology. The main focus of such models is on discontinuities (ruptures, collapses, shocks, etc.) in dynamic systems, caused by smooth changes in the control variables. Such jumps (bifurcations) may merge, if - given a certain range of the control variables - a specific set of values of the state variables (see, for instance, Amson, 1975; Dendrinos and Mullally, 1983; and Wilson, 1981).

B. Disaggregate Models

(a) Micro simulation models: Micro simulation models have mainly been designed to describe or forecast dynamic spatial processes of individuals (or homogeneous groups). Such simulation experiments are especially necessary, if no micro survey information on individual behaviour is available (see Wegener, 1980). These micro simulation models have proven to be useful tools in case of absence of information on disaggregate spatial preferences and perceptions.

(b) Conventional utility maximizing models: The category of utility maximizing models is based on the assumption that each actor in a geographical space maximizes his or her utility (usually in a deterministic sense) by choosing a spatial interaction patterns (e.g., spatial mobility, transportation) within constraints emerging inter alia from income and time budgets. A good example of a utility maximizing model based on a multistage-multiactor optimal control spatial choice analysis can be found in Leonardi (1983). Another interesting illustration is offered by Zahavi (1979), who has designed a model in which the total distances covered by specific transport modes on an average day by an average traveler are maximized by using a mix of transport modes subject to upper bounds of travel time and money.

(c) Conventional random utility models: Random utility models take for granted that spatial choices are resulting from rational behaviour based on a stochastic utility evaluation of different spatial choice items. Usually the observed micro choices regarding disaggregate spatial behaviour are related to objectively measurable attributes of actors and of spatial choice items. Random utility models then provide a probabilistic explanation of discrete spatial choice behaviour. Conventional random utility models have mainly been based on a logit formulation (see for instance Ben-Akiva, 1973; and Domencich and McFadden, 1975). A major advantage of these models was their ability to deal with categorical and qualitative data in spatial choice processes (see also Wrigley, 1979), although it was more difficult to include subjective micro aspects such as habits, expectations, learning processes, policy impacts, and the like.

(d) Adjusted random utility models: This new class of random utility models aims to include especially the qualitative aspects of individual spatial choice behaviour for both explanatory and forecasting reasons. In this regard the family of General Extreme Value models (see McFadden, 1978) and the Multinomial Probit model (see Daganzo, 1979) are worth mentioning. These models allow inter alia a more flexible specification, the inclusion of panel data, and a straightforward aggregation toward homogeneous subgroups. However, the calibration of such models in case of many choice items and the interpretation of the outcomes of such models are more cumbersome.

(e) Psychometric behavioural models: This class of models encompasses inter alia socio-psychological and psychometric models focusing attention on individual psychological responses or attitudes regarding choice possibilities. Both direct preference (ex ante) methods and revealed preference (ex post) methods may be used (see Hartgen, 1974). Examples of models developed in this context are the elimination by aspects model (see Tversky, 1972) and experimental conjoint measurement models (see Dix, 1981). In general however, these models have great difficulties in reconciling attitudinal responses and observed behaviour, even in a dynamic context (see Burnett and Hanson, 1979; Cadwallader, 1975; Damm, 1980; and Louviere and Meyer, 1981). Some of these psychometric micro models may be based on random utility notions.

(f) Activity-based choice models: Activity-based choice models are descriptive or forecasting models developed for comprehensive disaggregate spatial choice analysis, in which instead of separate trips, a chain of trips related to a daily activity pattern of an actor is taken into account. Models of this type pay much attention to time allocations, scheduling of activities, constraints on movements and activity choice, interactions between decisions and by different actors, and dynamic spatial processes. Clearly, these methods are based on space-time geography developed by Hagerstrand (1970). Examples of activity-based choice models can be found in Carpenter and Jones (1983), Damm (1982), Dix (1981), Hensher and Stopher (1979), Van der Hoorn (1983), Jones (1977) and Lerman (1979). The majority of these models is based on household survey and panel techniques.

(g) Search models: This class of models regards spatial choice processes as dynamic spatial search processes. Clearly, in these types of models much attention is focused on the specification of choice items (alternatives), the definition of explanatory variables for choice processes, the judgement of all relevant alternatives, the size of transition costs, and the potential willingness to consider a spatial movement (see for instance Clark and Smith, 1982; Rogerson, 1983; and Weibull, 1978, 1982). These models may also be complementary to the abovementioned classes of models.

It should be added that the foregoing brief survey of spatial choice models is by no means exhaustive. Furthermore, various specific models may fall into more than one category (see also Van Lierop and Rima, 1985; and Van Lierop, 1986).

Having discussed some major classes of spatial choice and interaction models, we will defend in the next section the use of micro-oriented spatial choice models, and more particularly random utility models.

4. A CHOICE FOR DISAGGREGATE SPATIAL CHOICE MODELS

Spatial activity, mobility and interaction patterns exhibit a complexity that can hardly be analysed by means of conventional aggregate choice models. The great variety in actors, preferences, perceptions, spatial choice items and individual constraints leads to the need for a more disaggregate approach, through which all attributes of spatial choice analysis can be included in a detailed manner. Disaggregate choice models have received a great deal of interest in recent years. Compared to macro-oriented approaches, micro models have the following general advantages (see also Clark, 1983; Harsman and Snickars, 1975; Van Lierop and Nijkamp, 1980, 1982; and McFadden, 1978):

(a) a closer orientation toward behavioural approaches (see for instance, Burnett, 1973; Clark and Cadwallader, 1973; Downs, 1970; Golledge and Brown, 1967; Gould, 1973; Rushton, 1969; and Saarinen, 1976);

(b) a more precise description of actual spatial interactions which may take place at various aggregation levels (see for instance Stopher et al., 1981);

(c) a better possibility for analysing choice processes on a longitudinal, event-history or dynamic basis (see for instance, Coleman, 1981; Halperin, 1985; Koppelman and Pas, 1985; and Tuma and Hannan, 1984);

(d) a greater flexibility in specifying choice processes compared to traditional approaches, without making stringent assumptions regarding equilibrium, competition, or homogeneous land use (see also McDonald, 1979; De Palma and Ben-Akiva, 1981; and Smith and Clark, 1982);

(e) a more effective way of testing the statistical validity of empirical results from surveys or questionnaires (see for instance, Hensher and Johnson, 1981; and Manski and McFadden, 1981);

(f) a better way of including qualitative information on spatial choice processes in explanatory models (see Wrigley, 1984);

(g) a more satisfactory representation of public policy impacts on micro spatial choice processes (see Van Lierop and Rima, 1985; and Quigley, 1979);

(h) a more adequate representation of the dependence of the utility of an actor on the decision of all other actors including agglomeration and congestion effects (see Miyao and Shapiro, 1981).

Clearly, there is also a price to be paid for using disaggregate choice models: the complexity of model design and calibration increases, while also the computational costs may become fairly high.

In general, disaggregate spatial choice analysis is based on micro survey data of a categorical nature. In such cases, it is necessary to use a probabilistic approach in order to assess the expected choice behaviour, based on the assumption of individual utility maximization.

In case of a random utility model for spatial choices, the assumption is made that the utility of a certain choice item is made up by two components: a deterministic component accounting for systematic effects emerging from observed choice factors and a random component accounting for effects from unobserved factors. By means of a random utility model one may predict the probability that an actor will choose a certain alternative, given the values of the observables. The class of random utility models may be further subdivided into:

- models with independent, identically distributed, error terms; examples are multinomial logit models and some elimination by aspects models;
- closed-form models without independent, identically distributed, error terms; examples are nested logit models, general extreme value models, and prominence theory of choice models;
- multinomial probit models.

In the seventies, one specific class of disaggregate discrete spatial choice models has received an important position in the literature on disaggregate spatial interaction and activity analysis, viz. the multinomial logit model. One of the major weaknesses of the frequently applied multinomial logit model is its "independence from irrelevant alternatives" (IIA) property, caused by restrictive assumptions on cross-substitution embodied in the structure of the logit model (see Van Lierop, 1986, and Wrigley, 1984).

Adjusted specifications of the abovementioned logit model can be found inter alia in the dogit model (see Gaudry and Dagenais, 1979), the decompositional multi-attribute preference model (see Timmermans, 1984), and the nested logit model as a special case of the generalized extreme value model (see Ben-Akiva and Lerman, 1979; Daly and Zachary, 1978; McFadden, 1979; Sobel, 1980; and Williams, 1977). Especially, the nested logit model has received a strong theoretical and empirical position, as it can readily handle correlated random components of utility and hence embodies more general properties of cross-substitution than the logit model without sacrifice of computational tractability (see also McFadden, 1978).

The most general, least restrictive of the various discrete choice models is the multinomial probit model (see Daganzo, 1979). This model allows the random components of utility of choice items to be correlated and to have unequal variances, while also random taste variations across individuals is permitted. The computational problems of multinomial probit models are however not easy to solve, though the Clark approximation to reduce the calibration problem to one of sequential univariate integration may be helpful in this respect (see also Sheffi et al., 1982).

As the multinomial probit model will be used in the empirical analysis of the present paper, a brief review of its essential features will be given here. The <u>general</u> features of this model (shared by all random utility models) are:

- the existence of a discrete set of choice items (alternatives);
- a partition of the population (the set of actors) into homogeneous subgroups, each having the same choice set and the same characteristics;
- the existence of an individual utility function which has to be maximized over the choice set by each actor;
- average utility is made up by the expected utility of all attributes characterizing a certain choice item;
- each utility function is composed of a deterministic component and a random component, so that the utility of an actor n with regard to a choice item i can be written as:

$$U_{in} = v(z_{in}) + \xi(z_{in}) \tag{1}$$

with:

U_{in} : utility of choice item i (i=1,...,I) for actor (n=1,...,N)

$v(z_{in})$: the deterministic part of the utility function of actor n, being determined by the vector of attributes of alternative i, z_{in}.

$\xi(z_{in})$: the random part of the utility function of actor n, representing individual utility differences emerging from taste variations, individual measurment errors, effects of missing data, misspecifications, etc.

Then the probability p_{in} that actor n selects an alternative is defined as:

$$p_{in}=\text{Prob}\{[v(z_{in})+\xi(z_{in})]\geq[v(z_{i'n})+\xi(z_{i'n})];i'=1,\ldots,I;\ i'\neq 1\}$$
$$i=1,\ldots,I;\ n=1,\ldots,N \tag{2}$$

The specific assumptions of the multinomial probit model are that the random terms in (2) are cumulative and normally distributed (see Daganzo, 1979; and Hausman and Wise, 1978). Hence this model allows the introduction of a dependent distribution for the random components by making specific assumptions about the structure of the variance-covariance matrix. One of the standard specifications of the variance-covariance matrix can be found in Hausman and Wise (1978), who assume that the variances for each alternative are proportional to the mean of each of them and that the covariances are proportional with the square root of the product of all the means of all relevant alternatives. In this way, individual taste variations and interdependencies among actors can be taken into account. Such a model can be estimated by means of maximum likelihood procedures, for instance, by means of the computer program CHOMP (see Daganzo and Schoenfeld, 1978), leading to consistent parameter estimates.

Altogether, the multinomial probit model has the following advantages over alternative discrete choice models (see Sheffi et al., 1982; Van Lierop, 1986, and Van Lierop and Rima, 1984):

- flexibility in specification by means of a full parametrization in terms of the covariance matrix, so that individual utility differences can be included and hence the 'independence from irrelevant alternatives' axiom can be avoided;
- introduction of taste variation by incorporating parameters that depend on the values of specific explanatory variables;
- statistical robustness by allowing the possibility of handling missing data and measurement errors;
- introduction of structural state dependence by including repeated observations, so that this model is extremely useful for panel and longitudinal data;
- possibility of consistent aggregation, so that aggregate utility for subgroups can easily be assessed.

Clearly, the use of a multinomial probit model has also some disadvantages:

- interpretation of results is usually not easy;
- large numbers of alternatives are difficult to calibrate.

Given the abovementioned remarks, the present authors have made a choice for the use of a multinomial probit model in order to analyse disaggregate spatial choices. In the sequel of this paper, some results of an empirical study on the Dutch housing market will be presented based on Van Lierop, 1986.

5. FEATURES OF THE DUTCH HOUSING MARKET STUDY

Several migration studies have shown that in general, the decision to migrate is the result of various determinants, such as a dissatisfaction with the present housing condition or with the local residential climate, more favourable perspectives on a labour market elsewhere, environmental quality (air or water pollution, noise annoyance, etc.) (see also, Onaka and Clark, 1983; Orishimo, 1982; and Schweitzer et al., 1976).

In the present analysis of residential choice on the Dutch housing market a distinction has been made between the potential decision to change dwelling (caused inter alia by a dissatisfaction regarding the present dwelling or the present job) and the actual decision to move. A potential decision to migrate only means that actors have a willingness or drive to move house, although it is not sure they will indeed change dwelling. This situation implies a conditional probability approach, in which the probability of an actor to actually change his residence is co-determined by his prior inclination to leave his present dwelling. Clearly, this prior inclination is a result of push and pull factors such as psychological perceptions and preferences regarding the attributes of the present dwelling including its neighbourhood quality and the quality of residential properties in relation to other dwellings. The four different conditional probabilities of actual moving behaviour given prior knowledge regarding the willingness to move can also be represented by means of the following 2 × 2 table:

Table 1. Conditional probability table of actual moving behaviour, given prior information on willingness to move.

		willingness to move	
		Yes	No
actual move	Yes		
	No		

The major aim of the housing market study for the Netherlands was to identify in a detailed (i.e., disaggregate) manner the relative importance of the determinants of individual residential choice decisions. In this study, individual preferences and perceptions regarding dwelling attributes (including locational factors) were analysed by means of micro discrete choice models. The following classes of actors on the demand side of the housing market were distinguished:

- potential migrants, subdivided into socio-economic or age classes, each specific class being mainly interested in a specific type of dwelling (i.e., a dwelling provided with a minimum level of various attributes);
- starting actors, subdivided into new households entering the housing market, and immigrants.

In the light of the limited supply of dwellings in each dwelling category and the large demand for dwellings in some categories, it is reasonable to assume that in the Dutch housing market context many actors ultimately decide to select a house that is essentially a second or third choice. The use of a disaggregate discrete choice model may then provide adequate insight into the motives of actors to move into dwellings of their second or third choice, so that planners are also informed of discrepancies between the set of dwellings of a specific type preferred by given household classes and the set of dwellings actually chosen by these households. In this respect, also the secondary supply (i.e., the supply of dwellings induced by filtering processes) on the housing market by dwelling type and for each household class may be taken into consideration.

In order to examine these processes, a sample of data on the Dutch housing market was analysed in a detailed way. These data have also been used to study housing preferences in the Netherlands by means of psychometric techniques (see Kuylen, 1980). For this purpose, panel data based on household inquiries in two successive periods were collected. This sample covered a large number of municipalities in the Netherlands. After a screening procedure this data set was used for the present empirical analysis. The municipalities concerned showed a large variation in terms of size, location, urbanization rate, growth rate, housing market regulations, and tension between supply and demand on the housing market. Hence this sample may be regarded as a fairly representative description of the Dutch housing market.

The first panel data were collected in 1977. This sample covered approximately 2000 households and provided detailed information on household characteristics, current dwelling attributes, and household preferences to migrate, so that more insight could be obtained into priority schemes of households concerning all relevant residential factors.

The second panel data were collected one year later, in 1978. This sample served to examine the stability of household judgements regarding dwelling attributes and to identify differences between the actual moving behaviour since 1977 and the dwelling and migration preferences reported in the first inquiry. This second sample focused attention on two specific groups from the first sample, viz. all potential movers and those households which were not willing to move in 1977 but yet had moved since then.[1] In addition, the attributes of the new dwelling were analysed in a detailed manner.

The distribution of potential movers in 1977 and actual movers in 1978 is represented in Table 2 (see for more details, Van Lierop, 1986).

Table 2. Distribution of potential and actual movers.

		Willingness to move in 1977.		
		Yes	No	Σ
actual moves in 1978	Yes	37	5	42
	No	102	963	1065
	Σ	139	968	1107

In the context of a housing market analysis for the Netherlands, another important element has to be mentioned. The Dutch housing market is highly institutionalized and totally dominated by regulations, so that the price mechanism plays only a limited role. By no means can the price or rent of a house be regarded as a representation of its relative scarcity. In order to arrive at an objective evaluation of dwellings as the basis for rent control, an extensive system of quality scores for dwellings has been designed in the Netherlands. This dwelling quality evaluation (d.q.e.) score approach is based on the assignment of standard scores to the attributes of a dwelling in a certain housing category. This multi-attribute housing evaluation system takes into consideration a wide variety of dwelling items (number of rooms, space, age, bathroom facilities, heating, distance to work and nearest shopping area, neighbourhood quality, etc.). By

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1) These so-called 'forced movers' are not taken into account in this paper.

adding up all individual scores for the successive attributes, the aggregate value of a dwelling can be represented by means of a total dwelling quality score. By means of this system (which was originally related to the actual rent level in 1977 in the Netherlands), the heterogeneous choice alternatives on the housing market can be characterized and mutually compared.

In addition to an objective quality score depending on observable attributes of the dwelling concerned, a subjective quality score may be defined that represents the perception of a household regarding all attributes of the present dwelling. This information may provide more insight into the motives of a household to choose a specific dwelling type. For this empirical study data on such subjective household attitudes were available. A comparison of objective and subjective quality scores across all 1107 households led to the following result (see Table 3):

Table 3. Differences between objective and subjective dwelling quality scores

	Number of households
objective quality score > subjective quality score	423
objective quality score < subjective quality score	666
objective quality score ≈ subjective quality score	18
TOTAL	1107

The data on subjective attitudes of households can also be used to explain residential mobility (by adjusting the objective scores by means of the subjective perception weights). More details on the quality score approach can be found in a publication of the Ministry of Housing and Physical Planning and the Ministry of Justice (MHPP and MJ) (1979) and Van Lierop (1986).

Given the foregoing information on the Dutch housing market study, it is clear that - in view of the disaggregate data on households, dwelling types, attributes, individual preferences and perceptions - research based on a disaggregate choice modeling approach is plausible, while in the present case the use of a multinomial probit model is preferred, especially because it is realistic to assume interrelations between many dwelling types on a (stringent) housing market, so that a model incorporating interdependencies between relevant alternatives is desirable. In this regard, the multinomial probit model, including a full variance-covariance matrix (the Hausman-Wise approach), may be regarded as a promising tool. Hence this approach was adopted for the empirical analysis of the Dutch housing market.

6. RESULTS OF THE DUTCH HOUSING MARKET STUDY

In this section some results of the housing market analysis in the Netherlands will be presented. In this project the following series of successive steps was inter alia considered:

(1) estimation, explanation and prediction of the willingness to move house in period t;

(2) conditional estimation, explanation and prediction of the actual moving behaviour in period t+1;

(3) further examination of dwelling alternatives;

(4) further examination of locational aspects.

These steps will be further discussed in successive sub-sections.

6.1 Willingness to move

The probability, p_{int}, that a certain actor n living in a dwelling of type i is willing to move in period t is equal to the probability that the expected utility of moving minus the disutility associated with transaction costs is larger than the expected utility of staying in the present house (see formula (2)).

The individual utility associated with residential mobility was assumed to be determined inter alia by the following explanatory factors:

- the "price/quality" ratio of the current dwelling i for household n;
- the "income/current housing costs" ratio for household n;
- the "family size/number of rooms" ratio of household n living in dwelling type i.
- the vacancy rate (or tension) perceived by household n on the housing market;

- the distance from the present dwelling i to work, as perceived by household n;
- the desire of household n to own a house instead of renting it;
- the transaction costs of moving from dwelling i as perceived by household n.

A careful study of the influence of these factors[1] - including a very detailed multicollinearity analysis for the first three ratios between which a high correlation was expected - showed that it is possible to explain and predict the willingness to move of individual households in a rather satisfactory way, by means of a fairly simple model including only the price/quality ratio as an exogenous variable.

The full estimation results and the predicted probabilities[2] of the relevant equations are presented in Table 4 under model number 1. Standard errors are given in brackets. They are all satisfactory. It should, however be remarked that the interpretation of these results is less easy than it may seem, as the calculation was not straightforward. The coefficient values are directly proportional to the standard deviations [3] of the random components of the utility functions. This is because at the start of the numerical approximation method of the CHOMP computer program, θ and ρ are assigned initial values (ρ some value between -1 and +1 and θ any positive value) and an increment that is used to calculate the partial derivatives needed for the search process. Without these initial values the para- meters of the probit model cannot be estimated. Hence the absolute values of the utility function coefficients are essentially arbitrary numbers (see also, Johnson and Hensher, 1982). Only the ratios between them have a definite meaning. Although it is clear that an increase of the price/quality ratio will result in an increase of the willingness to move, the degree to which this will happen is uncertain. A linear relationship, however, is - in view of the results - not likely. The constants in the model represent explanatory variables that have been left out of the model specification.

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1) For some factors data limitations prevented a real elaborate analysis for the entire population.
2) These results were calculated by means of an adapted version of the computer program CONFID (see: Sparmann and Daganzo, 1979).
3) In binary probit models those standard deviations must be set arbitrarily by normalization since they are not identifiable.

Table 4. Probit-estimations and predictions of:
- willingness to move (model number 1)
- the split probabilities of actually moving for households willing to move and households not willing to move (models 2 and 3, respectively)
- the probability of moving toward various classes of dwellings (model number 4)

(the table is explained in the text)

model number	sample size	alternatives	constant	price/ quality ratio	objective dwelling quality score	θ[1]	ρ_1[1]	ρ_2[2]	ρ_3[2]	max.log-likelihood	$\Sigma d^2/np_i$[4]	observed choices	predicted probabilities
1	1107	a. not-willing to move	0.33242 (0.00288)	1.23835 (0.05694)		0.13097	0.78493			-412.75	0.00027	0.87444	0.85927
		b. willing to move	0.11262 (0.00304)	1.15480 (0.02957)								0.12556	0.14073
2	968 not willing to move	a. not moved	0.47492 (0.08241)	0.67547 (0.03529)		0.01151	0.58421			- 30.02	0.000029	0.99483	0.99457
		b. moved	0.27619 (0.00339)	0.62383 (0.05340)								0.00517	0.00543
3	139 willing to move	a. not moved	0.28664 (0.00310)	0.59175 (0.20119)		0.09947	0.44257			- 77.83	0.000093	0.73381	0.72538
		b. moved	0.05333 (0.00085)	0.64614 (0.18046)								0.26619	0.27462
4	42	scores-class 1	-1.81150 (0.79003)		0.42160 (0.00022)							0.23180	0.20592[3]
		scores-class 2	1.07482 (0.06244)		0.40291 (0.10949)	0.01942	0.37091	0.11284	0.38999	- 38.99	0.000018	0.45238	0.51104
		scores-class 3	2.14478 (0.91926)		0.39022 (0.07106)							0.30952	0.27767

[1]) In the variance-covariance matrix of the multinomial probit model, θ describes the variance of the relevant alternatives and ρ the correlation between them.

[2]) Due to extension of the number of alternatives to 3, resulting in a higher-order variance-covariance matrix, ρ_2 and ρ_3 were introduced. (The variance-covariance matrix has been defined analogous to that for two alternatives.)

[3]) $\sum_{i=1}^{3} p_i \neq 1$; see Sparmann and Daganzo, 1979, page 7; or Daganzo, 1979, page 140.

The interpretation of the estimation results of this type of probit model should always take place in combination with an interpretation of the predicted probabilities. These probabilities fit the observed choices reasonably well, although an optimum connection certainly has not been reached.

Significance of results.

In the evaluation of the various explanatory variables listed at the beginning of this section a specific problem emanated, as for this type of probit model the usual calculation of standard errors is not very easy. The reason is that with an elaborate data set and more than two explanatory variables, Clark's approximation method, which is used in the computer program CHOMP, does not provide an easy calculation of the optimum. And only at the optimum can standard errors be derived.[1)]

One may use an alternative method to evaluate the significance of the results, which is especially valuable for those estimations for which no standard errors are available. This method is based on the presupposition that the optimum has approximately been reached when, after several iterations in the estimation procedure, the following three conditions are satisfied:

- the maximum log-likelihood value remains about the same;
- the squared sum of the derivatives divided by the number of parameters ($\Sigma_i d^2/np$; which is an indication of the distance from the optimum in the approximation method) does not differ too much from zero; and
- the values of the parameters remain fairly stable.

Then, statistical significance of independent variables can be determined by excluding the variables successively from the set of explanatory variables and by examining next whether the results for the three abovementioned specific conditions change considerably or not. (In particular, it is judged to be important whether or not the maximum log-likelihood value decreases significantly). This alternative for determining statistical significance through focusing on the iterative

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1) The reason is that at the optimum an approximation of the negative inverse of the Hessian can be used as an estimation of the variance-covariance matrix of the parameters.

procedure is judged to be very valuable. Unnecessary high costs and efforts can thus be avoided.

The connections between the predicted probabilities and the observed choices of model number 1 are not yet completely satisfactory. A simple explanation can be given for this phenomenon. Where specifications include many exogenous variables, the non-linearity of the probit model causes the predicted probabilities to be very close to the probability values for the mean household of the entire population (i.e., the household that is defined by the averages of all exogenous variables). When fewer explanatory variables are used, this adaptation does not apply. Thus, since the calculation of the probabilities requires the use of the averages of the explanatory variables, the predicted probabilities provide only some information about the average households. Consequently for a model with only a few exogenous variables, these predictions do not give an entirely reliable indication of the degree to which the model corresponds to reality. Nevertheless, model 1 is a satisfactory model for forecasting individual households' willingness to move, as can be checked by splitting up the sample population into 10 classes of the price/quality ratio of the 'old' dwelling. (See Van Lierop, 1986).

6.2 Actual moving behaviour

After a subdivision of the population into 2 classes, viz. (1) the 968 households that reported not to be willing to move in period t, and (2) the 139 willing to do so, for each of these groups separately several specifications were also tested for the analysis of the probability that households will actually move one period later in t+1. Exogenous variables included here were:

- the price/quality ratio;
- the income/current housing costs ratio;
- the family size/number of rooms ratio;
- a combination of the price/quality ratio and the income/current housing costs ratio;
- the perception of the suitability of the old dwelling.

All these alternatives scored reasonably well under the three additional criteria for evaluating the significance of multinomial probit results (specified at the end of subsection 6.1). Yet, here too the approach with only the price/quality ratio as a single exogenous variable next to a constant term, produced the best results. They are presented in Table 4 for model 2 and 3. It is worth noting from these results that:

- for households that were not willing to move in period t, the price/quality ratio had the largest influence on the decision not to move in period t+1 (see model 2), whereas for households that were willing to move, the price/quality ratio had the largest influence on the decision to actually move (see model 3);
- the predicted probabilities for both groups are very satisfactory.

Predictions in period t for the integral (or 'total') probabilities of moving or not in period t+1, can next be derived by multiplying the willingness to move probabilities for the entire population (from model 1) with the probabilities of actually moving for each of the specified groups (models 2 and 3). Table 5 presents these calculations.

Table 5. Calculation of integral probabilities of moving or not.

	predicted probability model 1		predicted probability model 2		predicted probability model 1		predicted probability model 3		integral probability of moving
1. prediction in t not to be moved in t+1	0.85927	×	0.99457	+	0.14073	×	0.72538	=	0.95669
2. prediction in t to be actually moved in t+1	0.85927	×	0.00543	+	0.14073	×	0.27462	=	0.04331

Table 6. Direct observed integral moving choices.

	observed choice model 1		observed choice model 2		observed choice model 1		observed choice model 3		integral observed choice
1. not moved in t+1	0.87444	×	0.99483	+	0.12556	×	0.73381	=	0.96206
2. moved in t+1	0.87444	×	0.00517	+	0.12556	×	0.26619	=	0.03794

For the observed choices there exists, of course, an equality between the sum of the products of the step-wise (conditional) choices and the direct integral observed choices. This can be seen from Table 6.

From this subsection we may conclude that the comparison of the predicted and the observed moving behaviour shows that a step-wise analysis (by studying households' willingness to move or not at first, and next the actual moving behaviour, if possible, separately for several household classes), provides a good basis for the prediction of moving patterns in the Dutch housing market.

6.3 Examination of dwelling alternatives

In this section an explanation of the choices of dwelling types of moving households and a prediction of these choices is given. Originally it was planned to divide the dwellings from the sample into a large number of classes of objectively defined dwelling quality evaluation (d.q.e.) scores (see section 5). These classes would be used for the analysis of dwelling choices instead of classes of dwelling types, especially because many housing market studies so far have had great difficulties in defining a good classification for dwelling types. D.q.e. scores offer a possibility to cover the entire spectrum of dwelling attributes, and to define the dwelling quality on a continuous scale, which can be divided into a great many parts (classes).

Although the limited sample size did not permit the definition of many classes, the analysis has been executed for three classes of d.q.e. scores. The major goal here is to illustrate the possibilities of this approach. Table 7 shows how the three classes of d.q.e. scores have been distinguished:

Table 7. Classes of dwelling quality evaluation scores.

class number	number of objectively measured d.q.e. scores	number of respondents from the sample	observed choices
1	> 160.0	10	0.23810
2	120.0 - 160.0	19	0.45238
3	< 120.0	13	0.30952

An attempt has been made to explain the choice of a specific type of dwelling by using various models specifications including the following exogenous variables:

- net income per month;
- the objectively measured d.q.e. score of the old dwelling;
- the subjectively measured d.q.e. score of the old dwelling;
- type of dwelling before the move.

The model that performed best (under the criteria defined in subsection 6.1) had as explanatory variable next to a constant term only the objective d.q.e. score of the old dwelling. The results are presented in Table 4 under model number 4.

If the subjective d.q.e. score was used as explanatory variable in model 4 instead of the objective one, the model did not explain equally well. Intuitively this does not seem plausible. Individual perceptions and evaluations are normally expected to have a big impact on whatever choice. It may however be possible that the definition of only three classes of d.q.e. scores is too broad to do justice to a really subjective evaluation procedure.

The integral probablities of moving <u>and</u> choosing one of the three classes of dwelling scores can be calculated by combining the results for alternative 2 in Table 5 with the outcome of model 4. This is illustrated in the upper part of Table 8. The lower part of the table presents an overview of the total of observed probabilities of moving <u>and</u> choosing specific dwelling score classes, resulting from combining the relevant information from Table 6 with the observed choices from model 4.

Comparison of the realized choices with the calculated integral probabilities in Table 8, shows that the predicted results with the small sample population and only three alternative classes of dwelling types are quite satisfactory. Only for dwelling score class 2 the predictions are significantly too high. This deviation (probably especially resulting from the already not very good fit between the predicted probabilities and the observed choices for model number 4) may be caused by the fact that the individual households in this small sample deviate too much from the mean household, which results in a poor fit between the predicted probabilities with the observed choices in models with just a few exogenous variables. This may be particularly true here as the objective d.q.e. scores can clearly result in a larger range of deviations than a limited set of dwelling types.

Table 8. Integral probabilities of moving and choosing a particular dwelling score class.

	integral moving probability Table 5		predicted probability model 4		predicted integral probabilities of moving and choosing a dwelling
dwelling scores-class 1:	0.04331	×	0.20592	=	0.00892
dwelling scores-class 2:	0.04331	×	0.51104	=	0.02213
dwelling scores-class 3:	0.04331	×	0.27767	=	0.01203
	observed choices Table 6		observed choices model 4		observed integral probabilities of moving and choosing a dwelling
dwelling scores-class 1:	0.03794	×	0.23810	=	0.00903 (=10/1107)
dwelling scores-class 2:	0.03794	×	0.45238	=	0.01716 (=19/1107)
dwelling scores-class 3:	0.03794	×	0.30952	=	0.01174 (=13/1107)

Dividing the set of dwellings into a series of d.q.e. scores of the 'old' dwelling in order to show that model 4 is still a good predictive model is difficult here, because of the small sample size, but an illustrative division into three classes for the 'old' dwellings (similar to the three classes of d.q.e. scores chosen from in this section) already shows promising results (see Tables 9 and 10).

Table 9. Household moves between classes of d.q.e. scores.

old (period t) dwelling	new (period t+1) choice alternative class 1	class 2	class 3	Total
class 1	3	2	0	5
class 2	5	7	4	16
class 3	2	10	9	21
Total	10	19	13	42

The probabilities resulting from applying model 4 to each of the nine separate classes defined by Table 9 are presented in Table 10.

Table 10. Split predictions of probabilities of choosing different classes of d.q.e. scores.

old (period t) dwelling	new (period t+1) choice alternative	observed choices	predicted probabilities
	class 1	0.60000	0.60125
class 1	class 2	0.40000	0.31900
	class 3	0.00000	0.07548
	class 1	0.31250	0.34938
class 2	class 2	0.43750	0.46135
	class 3	0.25000	0.18334
	class 1	0.09524	0.05221
class 3	class 2	0.47619	0.48868
	class 3	0.42857	0.45407

Some of the classes in Table 10 show reasonable fits between the realized choices and the predicted probabilities, at least better than before. The probability that a household will choose to move into a dwelling of class 1 when it lives in a dwelling of that class already, is the most likely of all probabilities. This is easily explained as class 1 is the class of the relatively highest quality and households usually do not like to move into a dwelling of lower quality.

The conclusion from this subsection is that the explanation and prediction of choices of dwelling alternatives leads to satisfactory results by means of a relatively simple model specification based on d.q.e. scores. Moreover this approach can avoid many of the problems which usually arise when the housing market is studied using a limited set of housing types.

6.4 Examination of locational aspects

The purpose of this phase was to analyse whether important geographical and quantifiable differences exist in the moving behaviour of households in the Dutch housing market.

In order to be able to execute some specific spatial analyses a much larger sample should have been available than the current study sample. A larger data set should ideally have contained various spatial groups, which would have allowed separate repetition of all the previous research phases (1-3). The limited sample in this study, however, allowed only modest spatial distinctions. The 1107 respondents from Table 2 were classified three times into two separate groups:

1.a. households in cities with 30,000 or more inhabitants, versus
   b. households in the countryside, villages, suburbs and small towns (less than 30,000 inhabitants);
2.a. households in the 'Randstad' (the entire urbanized part of the western part of the Netherlands), versus
   b. households in the rest of the country;
3.a. households in stringent (very regulated) housing market areas, versus
   b. households in areas with a relatively liberal (easier) housing market.

Further spatial diversified analyses of household classes or dwelling alternatives were not possible.

For each spatially distinguished class of the three groups the probabilities of both the willingness to move and actually moving have been predicted. The explanation of these items, however, has not been re-estimated. Instead, coefficients of the models from the former sections have been used to predict the relevant probabilities for the various spatial groups. In this paper we only present the results of the first groups.

It is striking to note (see Table 11) that hardly any differences exist between the groups in their willingness to move. The prediction of the actual moving behaviour was again done separately for the 968 households from Table 2 that were not willing to move and the 139 that wanted to do so. As an input for these predictions the estimates of the coefficients of models 2 and 3 from Table 4 were used. Table 12 shows the resulting predictions.

The predictions for the households that were not willing to move in period t give good approximations of the observed choices. Furthermore, no significant differences in the moving behaviour could be found between the spatial classes, i.e. households in large cities do not tend to move more frequently than anywhere else. It should also be remembered that the number of households which were not willing to move but which actually moved is very low in the sample.

The fits between the predictions and the realized choices were slightly less satisfactory for households that were willing to move. The extent to which they have actually moved is slightly higher in

Table 11. Predictions of willingness to move of spatially diversified groups.

households that lived in period t in	number of respondents	alternatives	number of respondents per alternative	observed choices	predicted probabilities
a. cities	668	a. not willing to move	584	0.87425	0.88005
		b. willing to move	84	0.12575	0.11995
b. elsewhere	439	a. not willing to move	384	0.87472	0.87213
		b. willing to move	55	0.12528	0.12787

Table 12. Predictions of actual moves of spatially diversified groups.

	households that lived in period t in	number respondents	alternatives	number respondents per alternative	observed choice	predicted probabilities
A. Households not willing to move in period t	a. cities	584	a. not moved	580	0.93315	0.99484
			b. moved	4	0.00685	0.00516
	b. elsewhere	384	a. not moved	383	0.99740	0.99418
			b. moved	1	0.00260	0.00582
B. Households willing to move in period t	a. cities	84	a. not moved	60	0.71429	0.73934
			b. moved	24	0.28571	0.26066
	b. elsewhere	55	a. not moved	42	0.76364	0.70588
			b. moved	13	0.23636	0.29412

cities, than elsewhere. Predictions and observed choices, however, do not show the same pattern in this respect. It is possible that disturbances arise here, which are again caused by the small sample size, or by the fact that the model specification contained only one exogenous variable with a constant term (resulting in comparable prediction problems as encountered in the discussion of Table 9 in the previous subsection).

It is interesting to observe in a comparison of Table 12 with Table 11 that while there seem to be no differences in willingness to move between households in cities and elsewhere, the first group seems to be more often succesful in executing its plans.

The foregoing results have clearly demonstrated the potential of disaggregate discrete choice models (i.e., probit models) for analysing residential choices and behavioural patterns at a housing market. Further progress can be made by using dynamic discrete choice models (based on lagged perception variables), provided of course a set of appropriate data on residential choices and perceptions of households is available.

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